Some Advances and Challenges on *POPulation-Based Randomized* Optimization Algorithms (POP) for High-Dimensional Black-Box Optimization/Search (BBO)

Qiqi Duan, SUSTech & HIT, China

For LEAD Workshop (Virtual) at SCUT, China

In Sept. 13, 2025

LEAD Website: https://sites.google.com/view/leadworkshop2025/
My Personal Website: https://evolutionary-intelligence.github.io/

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PyPop7: A Pure-Python Library for Population-Based Black-Box Optimization

Qiqi Duan, Guochen Zhou, Chang Shao, Zhuowei Wang, Mingyang Feng, Yuwei Huang, Yajing Tan, Yijun Yang, Qi Zhao, Yuhui Shi;
25(296):1−28, 2024.

Abstract

In this paper, we present an open-source pure-Python library called PyPop7 for black-box optimization (BBO). As population-based methods (e.g., evolutionary algorithms, swarm intelligence, and pattern search) become increasingly popular for BBO, the design goal of PyPop7 is to provide a unified API and elegant implementations for them, particularly in challenging high-dimensional scenarios. Since these population-based methods easily suffer from the notorious curse of dimensionality owing to random sampling as one of core operations for most of them, recently various improvements and enhancements have been proposed to alleviate this issue more or less mainly via exploiting possible problem structures: such as, decomposition of search distribution or space, low-memory approximation, low-rank metric learning, variance reduction, ensemble of random subspaces, model self-adaptation, and fitness smoothing. These novel sampling strategies could better exploit different problem structures in high-dimensional search space and therefore they often result in faster rates of convergence and/or better qualities of solution for large-scale BBO. Now PyPop7 has covered many of these important advances on a set of well-established BBO algorithm families and also provided an open-access interface to adding the latest or missed black-box optimizers for further functionality extensions. Its well-designed source code (under GPL-3.0 license) and full-fledged online documents (under CC-BY 4.0 license) have been freely available at https://github.com/Evolutionary-Intelligence/pypop and https://pypop.readthedocs.io, respectively.

[abs][pdf][bib] [code]

PyPop7 has been used and/or cited in one **Nature** paper [Veenstra et al., Nature, 2025] and etc. For any questions or helps, please directly use Discussions.

JMLR 2024 | arXiv 2022 | Jan26 2021 | PyPI pypop7 | docs passing | downloads 89k | visitors 67557 | Python | Linux | MacOS | Windows | CircleCI | GitHub Actions | Codecov | PyCharm | pytest | awesome | Sphinx | WeChat | CCF A

Just To Name a Few

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The Need for Open Source Software in Machine Learning

Sören Sonnenburg, Mikio L. Braun, Cheng Soon Ong, Samy Bengio, Leon Bottou, Geoffrey Holmes, Yann LeCun, Klaus-Robert Müller, Fernando Pereira, Carl Edward Rasmussen, Gunnar Rätsch, Bernhard Schölkopf, Alexander Smola, Pascal Vincent, Jason Weston, Robert Williamson; 8(81):2443−2466, 2007.

Abstract

Open source tools have recently reached a level of maturity which makes them suitable for building large-scale real-world systems. At the same time, the field of machine learning has developed a large body of powerful learning algorithms for diverse applications. However, the true potential of these methods is not used, since existing implementations are not openly shared, resulting in software with low usability, and weak interoperability. We argue that this situation can be significantly improved by increasing incentives for researchers to publish their software under an open source model. Additionally, we outline the problems authors are faced with when trying to publish algorithmic implementations of machine learning methods. We believe that a resource of peer reviewed software accompanied by short articles would be highly valuable to both the machine learning and the general scientific community.

[abs][pdf][bib]

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DEAP: Evolutionary Algorithms Made Easy

Félix-Antoine Fortin, François-Michel De Rainville, Marc-André Gardner, Marc Parizeau, Christian Gagné; 13(70):2171−2175, 2012.

Abstract

DEAP is a novel evolutionary computation framework for rapid prototyping and testing of ideas. Its design departs from most other existing frameworks in that it seeks to make algorithms explicit and data structures transparent, as opposed to the more common black-box frameworks. Freely available with extensive documentation at http://deap.gel.ulaval.ca, DEAP is an open source project under an LGPL license.

[abs][pdf][bib] [code]

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PyBrain

Tom Schaul, Justin Bayer, Daan Wierstra, Yi Sun, Martin Felder, Frank Sehnke, Thomas Rückstieß, Jürgen Schmidhuber, 11(24):743−746, 2010.

Abstract

PyBrain is a versatile machine learning library for Python. Its goal is to provide flexible, easy-to-use yet still powerful algorithms for machine learning tasks, including a variety of predefined environments and benchmarks to test and compare algorithms. Implemented algorithms include Long Short-Term Memory (LSTM), policy gradient methods, (multidimensional) recurrent neural networks and deep belief networks.

[abs][pdf][bib]

What is Black-Box Optimization (BBO)?

- To *properly* answer this seemingly simple question
  - An *interdisciplinary* perspective may be needed to show its necessity
    - Applications
  - A *historical* perspective may help to deepen our understanding
    - Algorithms

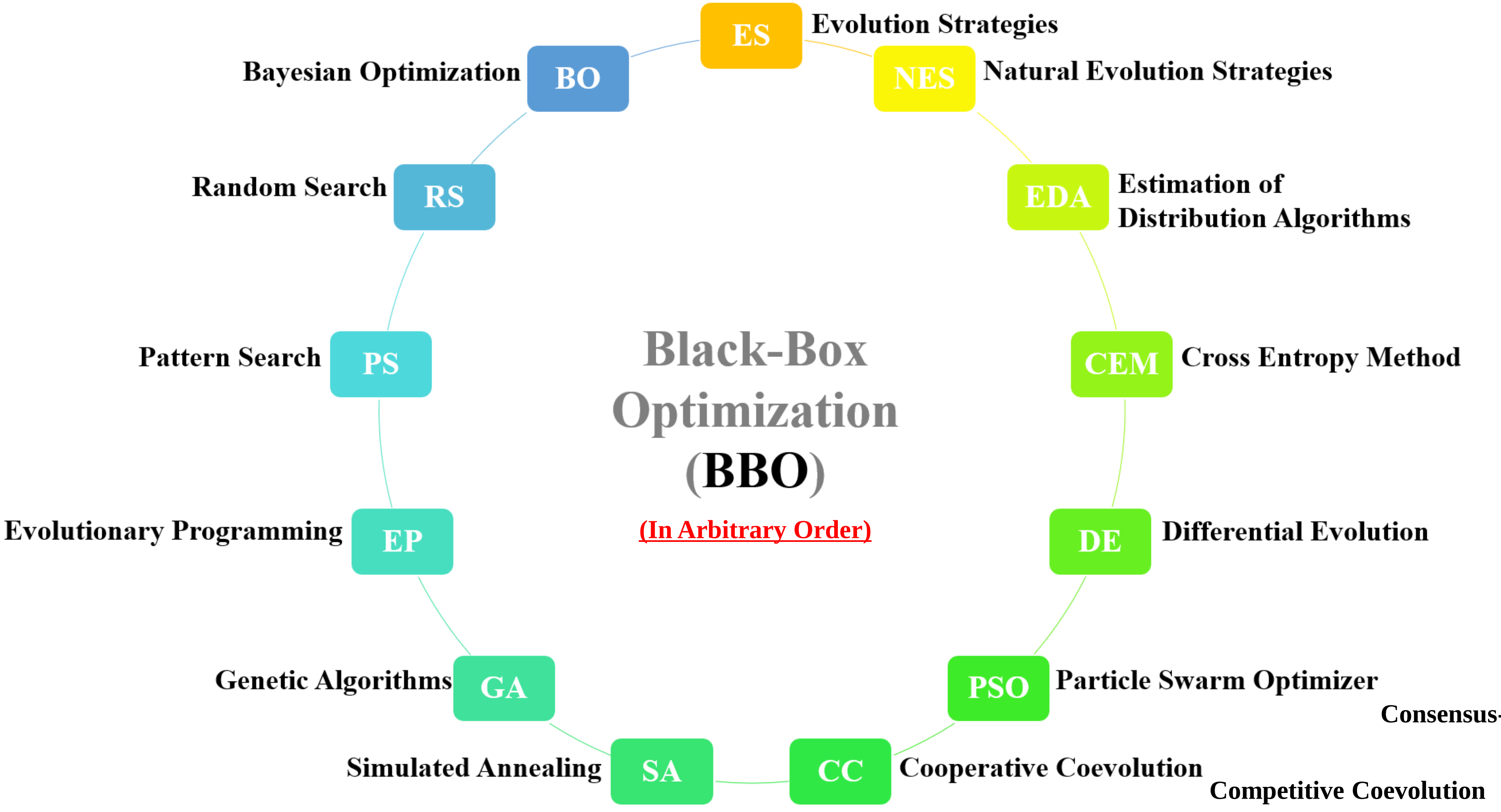
"In our opinion, the main fact, which should be known to any person dealing with optimization models, is that in general, optimization problems are unsolvable. This statement, which is usually missing in standard optimization courses, is very important for understanding optimization theory and the logic of its development in the past and in the future."---From **Prof. Yurii Nesterov (Member of National Academy of Sciences, USA)**

Name and Field Diversity in BBO (NOTE that *subtle differences* between them are not considered here)

- Derivative-Free Optimization
- Direct Search
- Experiment Design
- Generation-And-Test
- Global Optimization
- Gradient-Free Optimization
- Monte Carlo-Based Optimization
- Nondifferentiable Optimization
- Optimization Without Derivatives
- Random Search/Optimization
- Simulation-Based Optimization
- Zeroth-Order Optimization
- *Welcome to supplement* > Hybridization

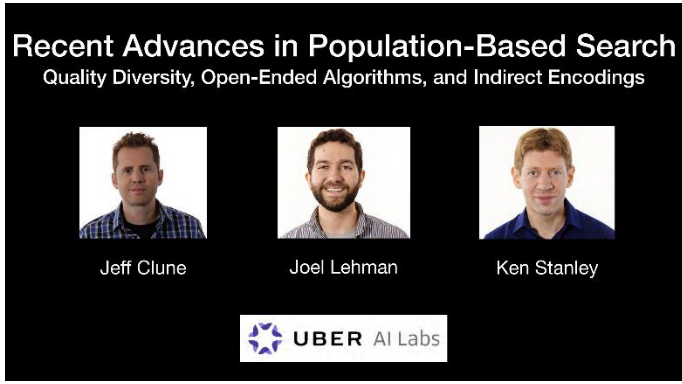
Academic Society (NOT complete):
AC: IEEE Control Systems Society (TAC) + International Federation of Automatic Control (Automatica);
AM: Society for Industrial and Applied Mathematics (SIOPT / SICON);
EC: ACM Special Interest Group on Genetic and Evolutionary Computation (TELO / GECCO / FOGA) + IEEE Computational Intelligence Society (TEVC / CEC / SSCI) + (ECJ);
ML: International Machine Learning Society (ICML) + (NeurIPS / ICLR);
MH/SC: (ASOC / PPSN / ICM);
MO: Mathematical Programming Society (Util 2010) / Mathematical Optimization Society (MP / MPC);
OR: Institute for Operations Research and the Management Sciences (OR / IJOC);
RL: (RLJ / RLC);
S: American Statistical Association + Royal Statistical Society;
SI: (SIJ / IJSIR / CIJ / ANTS / ICSI);
……

Algorithm Diversity in BBO (NOTE that *not all* of algorithm choices are considered here: Obtaining an *enumerative* list is really hard)



Dimensions of classification:

- **Individual vs Population**
- **Deterministic vs Randomized**
- **Model-Based vs Model-Free**
- ……



https://icml.cc/media/icml-2019/Slides/4336.pdf

Consensus-Based Optimization (CBO) [Fornasier et al., 2024, SIOPT]

Algorithm Diversity

- Campelo, F. and Aranha, C., 2023. Lessons from the evolutionary computation Bestiary. Artificial Life, 29(4), pp.421-432.
- Swan, J., Adriaensen, S., Brownlee, A.E., Hammond, K., Johnson, C.G., Kheiri, A., Krawiec, F., Merelo, J.J., Minku, L.L., Özcan, E., Pappa, G.L., et al., 2022. Metaheuristics "in the large". European Journal of Operational Research, 297(2), pp.393-406.
- Kudela, J., 2022. A critical problem in benchmarking and analysis of evolutionary computation methods. Nature Machine Intelligence, 4(12), pp.1238-1245.
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- de Armas, J., Lalla-Ruiz, E., Tilahun, S.L. and Voß, S., 2022. Similarity in metaheuristics: A gentle step towards a comparison methodology. Natural Computing, 21(2), pp.265-287.
- Sörensen, K., Sevaux, M. and Glover, F., 2018. A history of metaheuristics. In Handbook of Heuristics (pp. 791-808). Springer, Cham.
- Sörensen, K., 2015. Metaheuristics—the metaphor exposed. International Transactions in Operational Research, 22(1), pp.3-18.

Dr. Glover is an elected member of the [U.S. National Academy of Engineering]() and is the recipient of the [John von Neumann Theory Prize](), the highest honor of the [Institute for Operations Research and the Management Sciences.]()

- 2025: The paradox of success in evolutionary and bioinspired optimization: Revisiting critical issues, key studies, and methodological pathways
- 2024: Research orientation and novelty discriminant for new metaheuristic algorithms
- 2024: Metaheuristics exposed: Unmasking the design pitfalls of *** optimization algorithm in benchmarking
- 2024: Comprehensive taxonomies of nature- and bio-inspired optimization: Inspiration versus algorithmic behavior, critical analysis and recommendations (from 2020 to 2024)
- 2024: Exposing the *** optimization algorithm: A misleading metaheuristic technique with structural bias
- 2024: A literature review and critical analysis of metaheuristics recently developed
- 2023: Exposing the ***, ***, ***, ***, ***, and *** algorithms: six misleading optimization techniques inspired by bestial metaphors
- 2022: A new taxonomy of global optimization algorithms
- 2020: Nature inspired optimization algorithms or simply variations of metaheuristics?
- 2020: Benchmarking in optimization: Best practice and open issues
- 2019: Bio-inspired computation: Where we stand and what's next
- 2018: An insight into bio-inspired and evolutionary algorithms for global optimization: Review, analysis, and lessons learnt over a decade of competitions
- 2015: A critical analysis of the *** search algorithm—How not to solve sudoku
- 2014: How novel is the "novel" *** optimization approach?
- 2011: A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms
- 2011: Analytical and numerical comparisons of ***-based optimization and genetic algorithms
- 2010: A rigorous analysis of the *** search algorithm: How the research community can be misled by a "novel" methodology

From https://en.wikipedia.org/wiki/Fred_W._Glover

When to Use/Design BBO Algorithms?

- "BBO methods are *sometimes* employed for convenience rather than by necessity." [Larson et al., 2019, Acta Numerica]
- "Many of its customers would have gone elsewhere if they had been asked to specify the first derivatives." [Powell, 1998, Acta Numerica]

<u>(Just to name a few)</u>

- Berahas, Byrd and Nocedal, 2019. *Derivative-free optimization of noisy functions via quasi-Newton methods*. SIAM Journal on Optimization.
- Larson, Menickelly and Wild, 2019. *Derivative-free optimization methods*. Acta Numerica.
- Conn, Scheinberg and Vicente, 2009. *Introduction to derivative-free optimization*. Society for Industrial and Applied Mathematics. (Cited by > 2K)
- Powell, 1998. *Direct search algorithms for optimization calculations*. Acta Numerica.
- ……

Black-Box Optimizers (BBO)

- "The main lesson of the development of our field in the last few decades is that efficient optimization methods can be developed only by intelligently employing the structure of particular instances of problems." ---From **BOOK 'Lectures on Convex Optimization' of Prof. Yurii Nesterov (Member of National Academy of Sciences, USA) in [Springer-2018]**
- "Optimization algorithms are often designed for a specific type of search space, exploiting its specific structure." ---From **PAPER 'Information-Geometric Optimization Algorithms: A Unifying Picture via Invariance Principles' of Nikolaus Hansen (Inventor of CMA-ES) et al in [JMLR-2017]**

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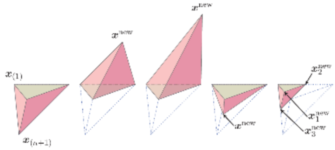

Pattern/Direct Search (PS/DS)

- **Fermi and Metropolis, 1952. *Numerical solution of a minimum problem*. TR, Los Alamos Scientific Lab.**
  - **https://www.nobelprize.org/prizes/physics/1938/fermi/biographical/ (Nobel Prize in Physics 1938)**
  - **https://history.computer.org/pioneers/metropolis.html (Computer Pioneer Award)**
- **Hooke and Jeeves, 1961. *"Direct search" solution of numerical and statistical problems*. JACM. (Cited by > 6K)**
- **Powell, 1964. *An efficient method for finding the minimum of a function of several variables without calculating derivatives*. CJ.**
  - **https://royalsocietypublishing.org/doi/10.1098/rsbm.2017.0023 (Member of RS and NAS)**
- **Nelder and Mead, 1965. *A simplex method for function minimization*. CJ. (Cited by > 41K)**
- **Wright, 1996. *Direct search methods: Once scorned, now respectable*. Pitman Research Notes in Mathematics Series.**
  - **https://www.simonsfoundation.org/people/margaret-h-wright/ (Member of NAS and NAE)**
- **Lagarias, Reeds, Wright and Wright, 1998. *Convergence properties of the Nelder--Mead simplex method in low dimensions*. SIOPT. (Cited by > 10K)**
- **Powell, 1998. *Direct search algorithms for optimization calculations*. AN.**

https://github.com/Evolutionary-Intelligence/pypop?tab=readme-ov-file#patterndirect-search-psds

Randomized Search/Optimization (RS/RO): Part 1 – AC / OR / MP

- Ashby, 1952. *Design for a brain: The origin of adaptive behaviour*. Springer. (Cited by > 6K)
  - https://ashby.info (A Pioneer in Cybernetics and Systems Theory)
- Brooks, 1958. A discussion of random methods for seeking maxima. OR.
- Rastrigin, 1963. *The convergence of the random search method in the extremal control of a many parameter system*. A&RC.
- Matyas, 1965. *Random optimization*. A&RC.
- Schumer and Steiglitz, 1968. *Adaptive step size random search*. TAC.
  - https://www.cs.princeton.edu/~ken/ (ACM/IEEE Fellow)
- Solis and Wets, 1981. *Minimization by random search techniques*. MOR. (Cited by > 2K)
- Zhigljavsky and Pinter, 1991. *Theory of global random search*. Springer.
- Zabinsky and Smith, 1992. *Pure adaptive search in global optimization*. MP.
  - https://www.informs.org/Recognizing-Excellence/Award-Recipients/Zelda-Zabinsky (INFORMS Fellow)
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- Stich, 2014. *On low complexity acceleration techniques for randomized optimization*. In PPSN. Springer.
  - https://www.sstich.ch/ (AE in JMLR)
- Wang, Hong, Jiang and Shen, 2025. *Gaussian process-based random search for continuous optimization via simulation*. OR.

https://github.com/Evolutionary-Intelligence/pypop?tab=readme-ov-file#random-searchoptimization-rsro

Randomized Search/Optimization (RS/RO): Part 2 – AI / ML / CM

- Schmidhuber, Hochreiter, and Bengio, 2001. *Evaluating benchmark problems by random guessing*. A Field Guide to Dynamical Recurrent Networks.
    - https://people.idsia.ch/~juergen/ (Neural Networks Pioneer Award 2016)
    - https://www.jku.at/en/institute-for-machine-learning (Neural Networks Pioneer Award 2021)
    - https://yoshuabengio.org/ (A.M. Turing Award Laureate 2018 / Neural Networks Pioneer Award 2019)
- Rosenstein, M.T. and Barto, A.G., 2001. *Robot weightlifting by direct policy search*. IJCAI.
    - https://amturing.acm.org/award_winners/barto_9471663.cfm (A.M. Turing Award Laureate 2024)
- Bergstra and Bengio, 2012. *Random search for hyper-parameter optimization*. JMLR. (Cited by >15K)
    - https://yoshuabengio.org/ (A.M. Turing Award Laureate 2018 / Neural Networks Pioneer Award 2019)
    - "Low Effective Dimensionality (LED)"
    - "The most promising and interesting direction … is certainly in adaptive algorithms": (Rechenberg, 1973; Hansen et al., 2003)
- Nesterov and Spokoiny, 2017. *Random gradient-free minimization of convex functions*. FoCM. (Cited by >1K)
    - https://www.nasonline.org/directory-entry/yurii-e-nesterov-5n5mo7/ (Member of NAS)
    - "The Seminal Article" + "A Particularly Striking Result" (Review Paper "Derivative-Free Optimization Methods" in 2019)
- Mania, Guy and Recht, 2018. *Simple random search of static linear policies is competitive for reinforcement learning*. NeurIPS.
- Sener and Koltun, 2020. *Learning to guide random search*. In ICLR.
- Gao and Sener, 2022. *Generalizing Gaussian smoothing for random search*. In ICML.

POPulation-Based Randomized Optimization Algorithms (e.g., EA/SI)

- Miikkulainen, R., 2025. Neuroevolution insights into biological neural computation. Science.
  - https://www.cs.utexas.edu/~risto/ (AAAI/IEEE/INNS Fellow + IEEE CIS Evolutionary Computation Pioneer Award 2020)
- Miikkulainen and Forrest, 2021. *A biological perspective on evolutionary computation*. Nature Machine Intelligence.
  - https://search.asu.edu/profile/3182641 (ACM-AAAI Allen Newell Award + IEEE Fellow + IEEE CIS Evolutionary Computation Pioneer Award 2023)
- Eiben and Smith, 2015. *From evolutionary computation to the evolution of things*. Nature.
  - http://www.evolutionarycomputation.org/
- Bonabeau, Dorigo and Theraulaz, 2000. *Inspiration for optimization from social insect behaviour*. Nature.
  - https://iridia.ulb.ac.be/~mdorigo/HomePageDorigo/index.php (AAAI/IEEE Fellow + IEEE CIS Evolutionary Computation Pioneer Award 2016)
- Forrest, 1993. *Genetic algorithms: Principles of natural selection applied to computation*. Science.
- Bounds, 1987. *New optimization methods from physics and biology*. Nature.

Evolution Strategies (ES) / *Natural Evolution Strategies* (NES) / *Persistent Evolution Strategies* (PES)

- Akimoto, Auger, Glasmachers and Morinaga, 2022. Global linear convergence of evolution strategies on more than smooth strongly convex functions. SIOPT.
- Vicol, Metz and Sohl-Dickstein, 2021. *Unbiased gradient estimation in unrolled computation graphs with persistent evolution strategies*. In ICML.
- Ye and Zhang, 2019. *Mirror natural evolution strategies*. arXiv.
- Salimans, Ho, Chen, Sidor and Sutskever, 2017. Evolution strategies as a scalable alternative to reinforcement learning. arXiv.
- Ollivier, Arnold, Auger and Hansen, 2017. *Information-geometric optimization algorithms: A unifying picture via invariance principles*. JMLR.
- Auger and Hansen, 2016. *Linear convergence of comparison-based step-size adaptive randomized search via stability of Markov chains*. SIOPT.
- Diouane, Gratton and Vicente, 2015. *Globally convergent evolution strategies*. MP.
- Wierstra, Schaul, Glasmachers, Sun, Peters and Schmidhuber, 2014. Natural evolution strategies. JMLR. (CEC-2008; ICML-2009)
- Bäck, Foussette and Krause, 2013. *Contemporary evolution strategies*. Springer.
  - Thomas Bäck: IEEE Fellow + IEEE CIS Evolutionary Computation Pioneer Award 2015
- Hansen, Müller and Koumoutsakos, 2003. *Reducing the time complexity of the derandomized evolution strategy with covariance matrix adaptation (CMA-ES)*. ECJ.
  - https://cse-lab.seas.harvard.edu/people/petros-koumoutsakos (Member of US National Academy of Engineering)
- Beyer and Schwefel, 2002. *Evolution strategies–A comprehensive introduction*. NC.
  - Hans-Paul Schwefel: IEEE Fellow + IEEE CIS Evolutionary Computation Pioneer Award 2002 (with Ingo Rechenberg)

Unbiased Gradient Estimation in Unrolled Computation Graphs with Persistent Evolution Strategies

Paul Vicol · Luke Metz · Jascha Sohl-Dickstein

Keywords: [Deep Learning]

Outstanding Paper

[Abstract] [Paper PDF]

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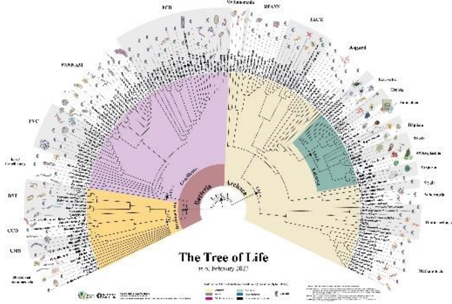
Abstract:
Unrolled computation graphs arise in many scenarios, including training RNNs, tuning hyperparameters through unrolled optimization, and training learned optimizers. Current approaches to optimizing parameters in such computation graphs suffer from high variance gradients, bias, slow updates, or large memory usage. We introduce a method called Persistent Evolution Strategies (PES), which divides the computation graph into a series of truncated unrolls, and performs an evolution strategies-based update step after each unroll. PES eliminates bias from these truncations by accumulating correction terms over the entire sequence of unrolls. PES allows for rapid parameter updates, has low memory usage, is unbiased, and has reasonable variance characteristics. We experimentally demonstrate the advantages of PES compared to several other methods for gradient estimation on synthetic tasks, and show its applicability to training learned optimizers and tuning hyperparameters.

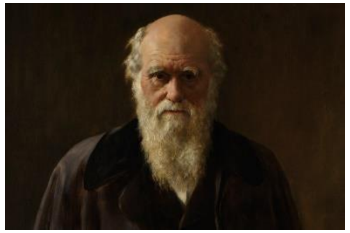
https://icml.cc/virtual/2021/poster/10175

Particle Swarm Optimizer (PSO) / *Consensus-Based Optimization* (CBO)

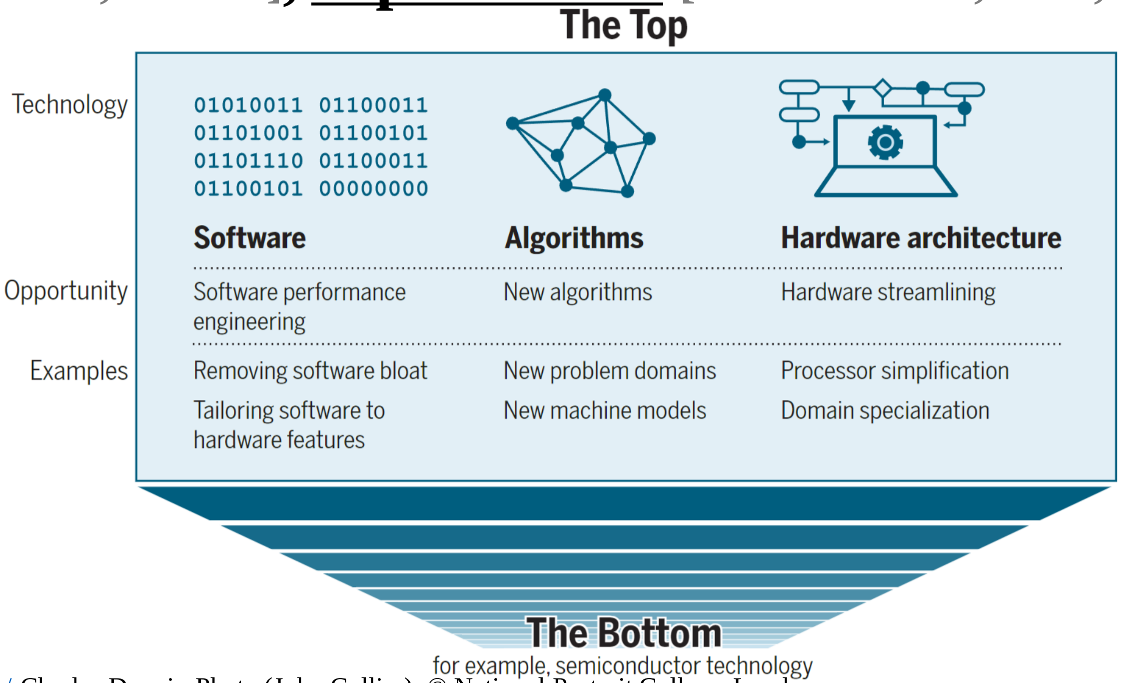
- **Bungert, Roith and Wacker, 2025. *Polarized consensus-based dynamics for optimization and sampling*. MP.**
- **Lyu and Chen, 2025. *Consensus based stochastic optimal control*. In ICML.**
- **Carrillo, Trillos, Li and Zhu, 2024. *FedCBO: Reaching group consensus in clustered federated learning through consensus-based optimization*. JMLR.**
- **Huang, Qiu and Riedl, 2024. *Consensus-based optimization for saddle point problems*. SICON.**
- **Bolte, Miclo and Villeneuve, 2023. *Swarm gradient dynamics for global optimization: the mean-field limit case*. MP.**
- **Borghi, Herty and Pareschi, 2023. *Constrained consensus-based optimization*. SIOPT.**
- **Fornasier, Huang, Pareschi and Sünnen, 2022. *Anisotropic diffusion in consensus-based optimization on the sphere*. SIOPT.**
- **Fornasier, Huang, Pareschi and Sünnen, 2021. *Consensus-based optimization on the sphere: Convergence to global minimizers and machine learning*. JMLR.**
- **Yuan and Yin, 2015. *Analyzing convergence and rates of convergence of particle swarm optimization algorithms using stochastic approximation methods*. TAC.**
- **Eberhart, Shi and Kennedy, 2001. *Swarm intelligence*. Elsevier. (Cited by >16K)**
- **Kennedy and Eberhart, 1995. *Particle swarm optimization*. In ICNN. (Cited by >90K)**

POPulation-Based Randomized Optimization Algorithms (e.g., EA/SI)





- **In accordance with the increase of computing power** (CPU/GPU/TPU/…)
  - **Ending of Moore’s Law** [Leiserson *et al.*, 2020, Science; Moore, 1998, PIEEE]
  - **RayES** [Moritz *et al.*, 2018, OSDI], **TianheDGA** [Fan *et al.*, 2020, Science], **FunSearch** [Romera-Paredes, 2024, Nature], **AlpahEvolve** [Novikov *et al.*, 2025, arXiv], ……



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https://www.apollo-magazine.com/4-things-to-see-charles-darwin/ Charles Darwin Photo (John Collier): © National Portrait Gallery, London
https://twitter.com/SGribaldo/status/1628431492459241472/photo/1 Tree of Life: © Bacille Diderm Beaud

Challenges in Distributed Optimization: *Interference from Interactions*

Science

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REPORT

Criticality and Parallelism in Combinatorial Optimization

WILLIAM G. MACREADY, ATHANASSIOS G. SIAPAS, AND STUART A. KAUFFMAN Authors Info & Affiliations

SCIENCE • 5 Jan 1996 • Vol 271, Issue 5245 • pp. 56-59 • DOI: 10.1126/science.271.5245.56

Abstract

Local search methods constitute one of the most successful approaches to solving large-scale combinatorial optimization problems. As these methods are increasingly parallelized, optimization performance initially improves but then abruptly degrades to no better than that of random search beyond a certain point. The existence of this transition is demonstrated for a family of generalized spin-glass models and the traveling salesman problem. Finite-size scaling is used to characterize size-dependent effects near the transition, and analytical insight is obtained through a mean-field approximation.

Journals & Magazines > IEEE Transactions on Parallel... > Volume: 35 Issue: 11

Distributed Evolution Strategies With Multi-Level Learning for Large-Scale Black-Box Optimization

Publisher: IEEE Cite This PDF

Qiqi Duan ; Chang Shao ; Guochen Zhou ; Minghan Zhang ; Qi Zhao ; Yuhui Shi **All Authors**

Abstract:
In the post-Moore era, main performance gains of black-box optimizers are increasingly depending on parallelism, especially for large-scale optimization (LSO). Here we propose to parallelize the well-established covariance matrix adaptation evolution strategy (CMA-ES) and in particular its one latest LSO variant called limited-memory CMA-ES (LM-CMA). To achieve efficiency while approximating its powerful invariance property, we present a multilevel learning-based meta-framework for distributed LM-CMA. Owing to its hierarchically organized structure, Meta-ES is well-suited to implement our distributed meta-framework, wherein the outer-ES controls strategy parameters while all parallel inner-ESs run the serial LM-CMA with different settings. For the distribution mean update of the outer-ES, both the elitist and multi-recombination strategy are used in parallel to avoid stagnation and regression, respectively. To exploit spatiotemporal information, the global step-size adaptation combines Meta-ES with the parallel cumulative step-size adaptation. After each isolation time, our meta-framework employs both the structure and parameter learning strategy to combine aligned evolution paths for CMA reconstruction. Experiments on a set of large-scale benchmarking functions with memory-intensive evaluations, arguably reflecting many data-driven optimization problems, validate the benefits (e.g., effectiveness w.r.t. solution quality, and adaptability w.r.t. second-order learning) and costs of our meta-framework.

Open Question: Collective (Swarm) Learning

ELSEVIER

Applied Soft Computing
Volume 166, November 2024, 112232

Cooperative coevolution for non-separable large-scale black-box optimization: Convergence analyses and distributed accelerations

Qiqi Duan[a,c,1], Chang Shao[b,c,1], Guochen Zhou[c], Haobin Yang[c], Qi Zhao[c], Yuhui Shi[c]

Pure Nash Equilibrium (PNE)

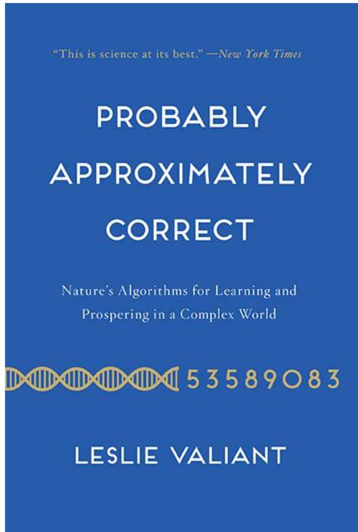
Main Theorem: Consider any partitioning solution $p = \{g_1, \ldots, g_m\}$ of a continuous-differentiable convex function $f(\mathbf{x}) \in C^1(\Omega, \mathbb{R})$, where Ω is an open convex set[10] in $\mathbb{R}^n$. For $f(\mathbf{x})$, all PNE (w.r.t. p) are equivalent to the global optima, and vice versa.

[10] Here it is implicitly assumed that there is (at least) one global optimum in this open convex set.

My Own (Not Necessarily Entirely Correct) Opinions on BBO (≠ Absolute Truth)

NOTE: I must admit and respect that other researchers have shown some and even all of the following opinions (in a deeper fashion) before my current representations.

- **Design principles** means generalization, although not always from the *explicit(supervision) learning* perspective
  - Invariance (CMA-ES, NES): PCA (unsupervision) / Natural Gradients (optimization)
  - Unbiasedness: under neutral selection
    Only with Online Adaptation
  - Meta-Training + Meta-Testing: PES / RL-Based / ……
  - But NOT as the absolute and even only performance criterion
- **Generalization** has its own boundary on the application range
  - Problem class *to be well solved* vs *to be not well solved*
  - Under NFLT [Wolpert&Macready, 1997, TEVC]
    - Under the *uniform* assumption (of all possible problem spaces)
  - Bounded generalization

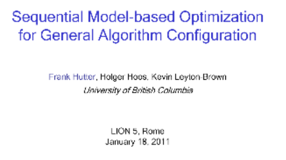


https://probablyapproximatelycorrect.com/

What Makes Some (Rather All) Algorithmic Versions of *Meta-Heuristics* Really "Stand Out (脱颖而出)"?: My Personal View

- Excel (Global or Local) Approximation Optimization/Search Abilities (vs Exact)
  - At least on one NP-Hard problem class (vs Over-Generalization)
  - Rather than on only one problem instance (or just few)
- Solid Design Principles
  - Rationality (logical and sometimes even philosophical insights)
  - Generalizability (at least on the *target* domain > bounded generalizability under NFLT)
- Rigorous Theoretical Foundations (e.g. via Mathematical Insights)
  - Although at the infancy stage, they are often lacked
  - When entering the mature stage, they are typically emerged
- Widely Accessible Open-Source or Commercial Implementations
  - From the author itself
  - From the others (further validation and improvement)
- Proper Problem-Solving (perhaps the main reason to criticize some MH papers)
  - Whether or not approximation is practically acceptable
  - Whether or not approximation is the only solution choice (in reasonable time)
- …… (*Welcome to supplement*)

Some of Other *Representative* BBO Algorithms Not Covered in This PPT


Sequential Model-based Optimization for General Algorithm Configuration

Frank Hutter, Holger Hoos, Kevin Leyton Brown
University of British Columbia

LION 5, Rome
January 18, 2011

https://aad.informatik.uni-freiburg.de/wp-content/uploads/papers/11-LION5-SMAC-slides.pdf

- **Sequential Model-Based Optimization (SMAC)**
  - **Lindauer, Eggensperger, Feurer, Biedenkapp, Deng, Benjamins, Ruhkopf, Sass and Hutter, 2022. *SMAC3: A versatile Bayesian optimization package for hyperparameter optimization*. JMLR.**
- **Simultaneous Perturbation Stochastic Approximation (SPSA)**
  - **Kleinman, Spall and Naiman, 1999. *Simulation-based optimization with stochastic approximation using common random numbers*. MS.**
- **Bayesian Optimization (BO)**
  - **Turner, Eriksson, McCourt, Kiili, Laaksonen, Xu and Guyon, 2021. *Bayesian optimization is superior to random search for machine learning hyperparameter tuning: Analysis of the black-box optimization challenge 2020*. NeurIPS.**
  - **Wang, Hutter, Zoghi, Matheson and De Feitas, 2016. *Bayesian optimization in a billion dimensions via random embeddings*. JAIR.**
- **…… (Just to name a few)**

Caution for This PPT Content ! (免责声明)

This PPT content reflects my limited and biased knowledge to Black-Box Optimization (BBO), Evolutionary Algorithms (EC), and Swarm Intelligence (SI), etc.

Any extensions, improvements, and corrections to this PPT content are very welcomed!

(Some parts of this PPT material come from my previous Tutorial on IEEE-CEC 2025 and also my own Ph.D. Dissertation. Finally, I acknowledge all references which have inspired this PPT content.)

The First Competition on Swarm Learning and Optimization (SLO) for Swarm Intelligence

- C-SLO(4SI) will be held on International Conference on Swarm Intelligence (ICSI) in 2026
  - Organizers:
    - Qiqi Duan (SUSTech, China)
    - Lijun Sun (SZTU, China)
    - Yang Shen (UTS, Australia)
    - Yuhui Shi (SUSTech, China)

ICSI ' 2026

IASEI

July 11 th– 14th, 2026
Chengdu, China

ANTS 2026

JUNE 8–10, DARMSTADT

www.ants2026.org

15TH INTERNATIONAL CONFERENCE ON SWARM INTELLIGENCE

First Call for Papers

Up-to-date information at https://ants2026.org

Conference Scope

Since its inception in 1998, ANTS has been a highly selective, single-track meeting that provided a forum for discussing advances in the field of swarm intelligence. It solicits submissions presenting significant, original research from researchers and practitioners of any area related to swarm intelligence.

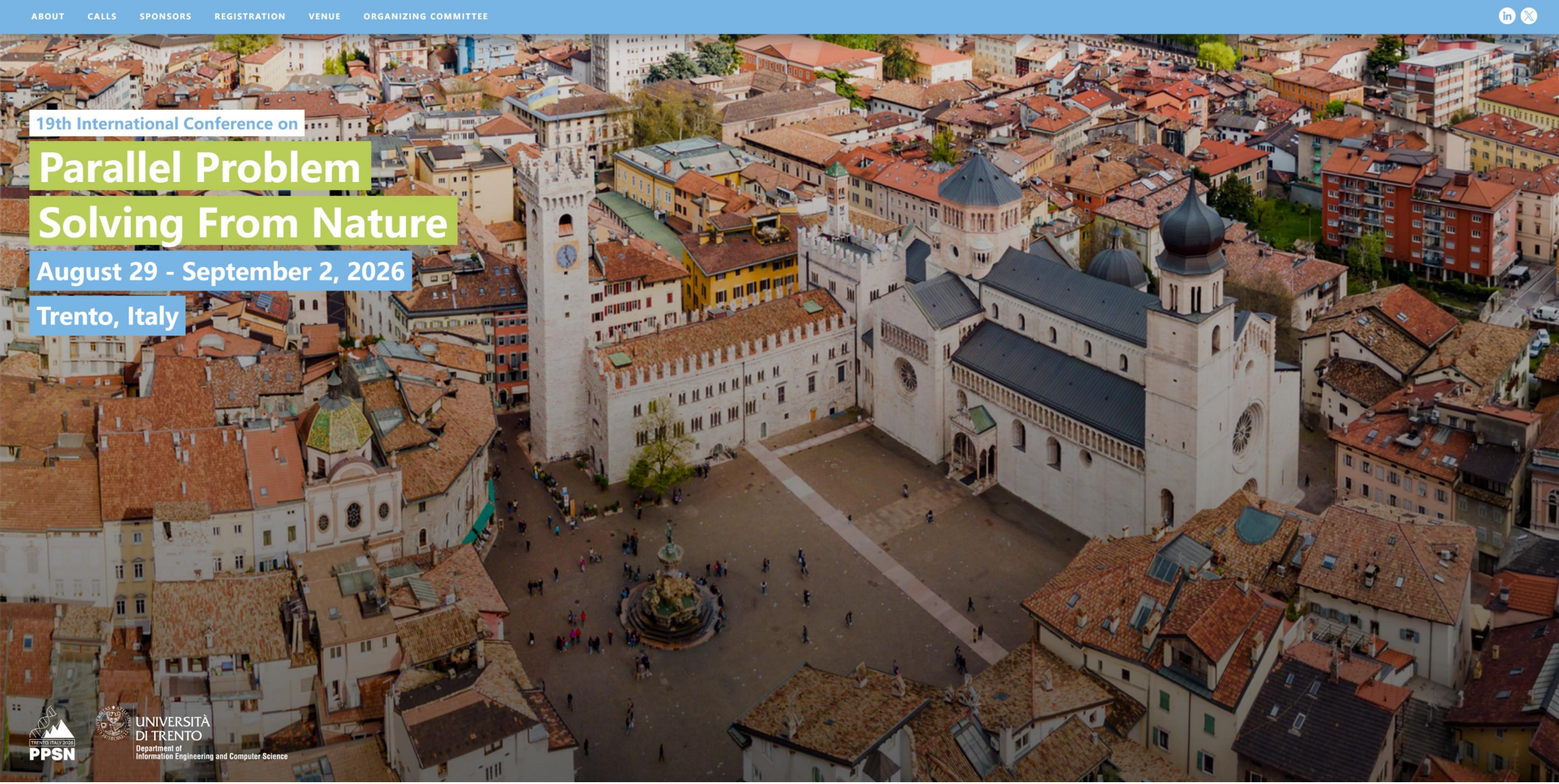
Swarm intelligence is an interdisciplinary and rapidly evolving field, rooted in the study of self-organizing processes in both natural and artificial systems. Researchers from disciplines ranging from ethology to statistical physics have developed models that explain collective phenomena, such as decision-making in social insect colonies and collective movements in human crowds. Swarm-inspired algorithms and methods have proven effective in solving complex optimization problems and creating multi-robot and networked systems of unparalleled resilience, adaptability and scalability. Applications of swarm intelligence continue to grow and become increasingly critical for addressing societal challenges such as environmental sustainability, food security, health, and global conflicts.

The 2026 edition’s theme is ***"reaching beyond - swarm intelligence across systems, disciplines, and communities"***. The meeting seeks to encourage new perspectives, help bridge traditional boundaries and enable open debate on what could be ambitious, exploratory, and groundbreaking endeavors to embark on.

Important Dates

Submission deadline:	November 10, 2025
Notification of acceptance:	January 30, 2026
Camera ready copy:	February 13, 2026
Conference:	June 8-10, 2026

https://ants2026.org/



https://ppsn2026.disi.unitn.it/

A Seminar on 30-Year Particle Swarm Optimization (PSO) Inspired by Swarm Intelligence (SI) from 1995 to 2025

This is a Seminar and Survery on 30-Year Particle Swarm Optimization (PSO) and its Same Kind (e.g., Consensus-Based Optimization) Inspired by Swarm/Collective Intelligence (SI) from 1995 to 2025 (Interesting Ideas Originally Proposed by J. Kennedy and R. Eberhart, and Further Developed by Prof. Shi et al.)